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Multidimensional Scaling Analysis of Controllers' Perceptions of Aircraft Performance Characteristics

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16. Abstract

Thirty full performance level (FPL) en route air traffic control specialists participated in an investigation of the salient features of aircraft mix, a proposed sector complexity factor. Controllers rated the "familiarity" (i.e., frequency of encounter) of 30 selected aircraft. They also provided weight class, engine number, engine type, cruising speed, climb, and descent rate estimates for each aircraft. A matrix of squared Euclidean distances derived from summary estimates (i.e., means of speed, climb, and descent) was used to construct a multidimensional scaling model of the aircraft. Multiple regression interpretation revealed that Dimension 1 was related to engine type, whereas Dimension 2 was associated with weight class. The position of elements in the derived stimulus space indicated that controllers may develop performance-related prototypes through the use of multiple cues derived from a number of sources. Results are presented as justification for further investigation into potential advantages of providing enhanced prediction cues (e.g., engine type and weight class) from a single source, which may increase the efficiency of controller decision making and decrease perceived workload.

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The domain of an en route air traffic control specialist (ATCS) is the sector. Sectors are defined both horizontally and vertically "and may overlie or underlie airspace controlled by another sector or approach control facility" (National Airspace System, 1995, p. 5:19). Note the irregular shape of the sector shown in Figure 1. This sector lies adjacent to others like one piece in a three-dimensional jigsaw puzzle. No two sectors are identical, and the relative complexity of each involves a complex interaction of sector geometry and traffic-related factors (Buckley, DeBaryche, Hitchner, & Kohn, 1983). Physical aspects (e.g., size, orientation of conflict points, airway configuration, terrain, limitations of radio or radar coverage) are considered in conjunction with traffic characteristics when sector boundaries are defined. This is due to the relationship between sector complexity and controller workload. "As contributors to task demand, sector characteristics can be thought of as workload generators. Workload is the controllers' subjective response to the 'objective' conditions which create sector complexity" (Mogford, Murphy, Roske-Hofstrand, Yastrop, & Guttman, 1994, p. 4).

During the validation stage of an investigation of controller workload models, five air traffic control specialists were asked to evaluate the relative difficulty of a set of sectors. They were also asked to provide explanations as to why they believed the sectors differed in complexity. Aircraft mix was one of 12 "difficulty factors" cited (Robertson, Grossberg, & Richards, 1979). These same factors were later used as the basis for an investigation of sector complexity relative to operational errors.[1] A group of 97 controllers and supervisors from the Chicago Air Route Traffic Control Center (ARTCC) was asked to estimate the degree to which each factor contributed to the complexity of their particular sector or area of specialization. Notably, aircraft mix was one of the highest-ranked factors in ten of the 30 sectors sampled (Grossberg, 1989).

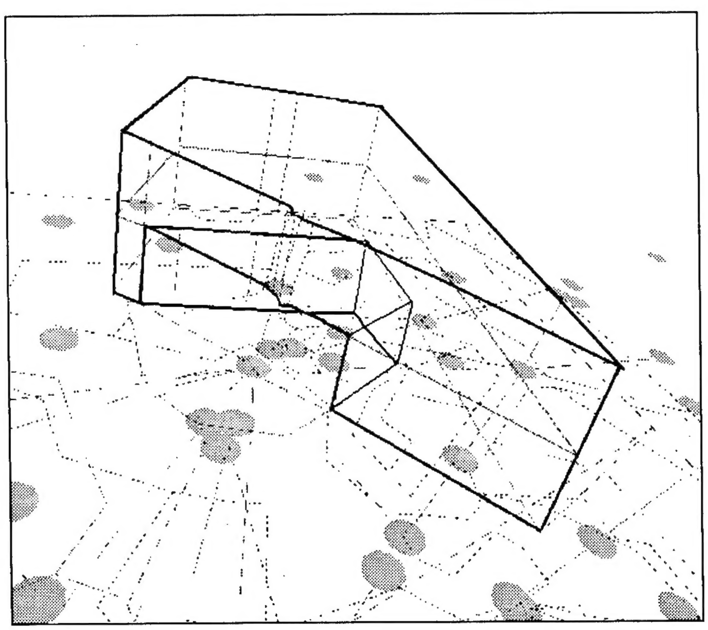

Figure 1. Air Route Traffic Control Center Sector Example

[1] An operational error occurs when an ATCS allows two or more aircraft to violate separation minima.

At the time, it was assumed that aircraft mix referred to problems associated with the disparate performance capabilities of propeller and jet aircraft. This assumption is consistent with sector design principles included in Appendix 2 of Order No. 7210.46, which imply that complexity is increased when aircraft with "vastly different performance characteristics" occupy a controller's airspace (Federal Aviation Administration, 1984, p. 2). Nevertheless, this interpretation may be incomplete or inaccurate. For example, what are the parameters of "vastly different?" What constitutes aircraft mix from a controller's perspective? Participants were never asked to elaborate on the salient features of aircraft mix in either of the studies cited. Consequently, it is possible that each controller's definition was not uniform.

Results of an investigation conducted at the Jacksonville ARTCC (Mogford, et al., 1994) offer limited insight into the potential components (or correlates) of aircraft mix. In the preliminary stages of the study, aircraft mix was defined as the proportion of commercial, private, and military traffic. The number of aircraft flying Visual Flight Rules (VFR) versus Instrument Flight Rules (IFR) was also considered to be a distinct factor. A subject matter expert who provided detailed factor definitions introduced engine type as an element of aircraft mix. In the final list of 19 "candidate" sector complexity factors, aircraft mix was defined as "VFR, IFR, props, turboprops, and jets, etc." (p. 37). Although this definition seems extensive, it may be neither comprehensive nor accurate. That is, verbal representations of aircraft mix may be only marginally related to the underlying dimensions of interest (see Payne, Bettman, & Johnson, 1993).

It is logical to assume that the availability of information would influence controllers' underlying representations as well as the expression of those representations. For example, engine type may be an excellent predictor of aircraft performance capabilities, but controllers do not have direct access to this information. On the other hand, controlled aircraft are accompanied by a datablock tag on the radarscope that displays, among other items, the aircraft identifier (AID). From this information, controllers may determine whether an aircraft is commercial, military, or private. For instance, commercial AIDs are recognizable because they correspond to flight numbers (e.g., AAL1550 represents American Airlines flight 1550). Military AIDs consist of a combination of pronounceable words and numbers, whereas privately-owned aircraft are distinguishable because they commonly fly under their aircraft registration number. Though all aircraft have registration numbers, only private (general aviation) aircraft are identified by them. Whether an aircraft is commercial, military, or general aviation is a fairly accurate predictor of engine type (ergo performance). Approximately 79% of all commercial aircraft are jets (International Civil Aviation Organization, 1995). Many military aircraft are also jets. In addition, military AIDs often indicate whether the aircraft is a high-performance jet or a larger aircraft designed for air transport. In contrast, general aviation aircraft are often, though not always, smaller, propeller-driven aircraft.

In addition to the AID, controllers are provided with partial information regarding an aircraft's weight class. There are three weight class categories: Heavy, Large, and Small. A single character (e.g., H), printed on the flight progress strip and available in the flight plan readout display, flags aircraft in the Heavy weight class. The reason controllers are provided with this information has to do with procedures associated with wake turbulence. However, weight class is also an imprecise indicator of engine type. Jets are somewhat more likely to be Heavy than are other engine types. Weight class may also serve as a predictor of climb and descent capabilities.

At best, AIDs and Heavy prefixes provide only a general indication of aircraft performance capabilities. However, controllers do have access to more specific information. For instance, aircraft type designators are alphanumeric labels that indicate the make and model of an aircraft (e.g., a B737 is a Boeing Model 737, a C150 represents a Cessna Model 150, and a BE77 is a Beech Skipper). Designators are printed on the flight progress strip and as part of the flight plan readout display. In addition, each aircraft's current speed is displayed on the datablock. Because fuel is expensive, most aircraft operate at average speeds that optimize fuel efficiency. As a result, controllers probably develop associations through repeated pairings of specific designators and average speed ranges. Simultaneously, broad classes of AIDs would be associated with both designators and speeds. A model of these proposed associations is provided in Figure 2.

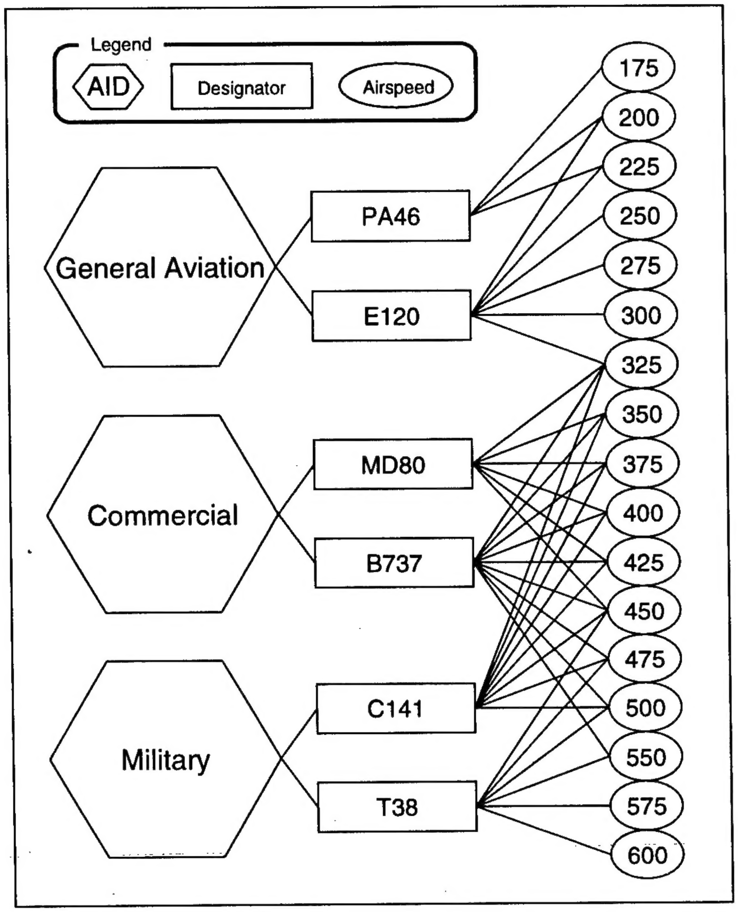

Figure 2. Model of Prototype Development

It would be parsimonious for controllers to develop prototypes based on this information, rather than rely on the recall of explicit ranges (Posner, Goldsmith, & Welton, 1967; Solso, 1991). The model in Figure 2 implies that performance-based prototypes would probably correspond to commercial, military, and private classifications, due to the salience and accessibility of the AID. Controllers' expectations of aircraft performance would then be based on comparisons with the prototypical aircraft within each category. It is likely that these groups would be characterized by graded membership and "fuzzy boundaries" because the performance of some aircraft would be more representative of the prototype than others (see Schwartz & Reisberg, 1991). Thus, an aircraft might be characterized as "a slow commercial jet," or "an average commercial jet," or "just like a commercial jet."

The model in Figure 2 also illustrates how air traffic controllers might use AIDs to predict aircraft performance. If broad classes of AIDs are associated with prototypes, an aircraft's AID could be used to calibrate performance estimates when the designator is not an effective cue (i.e., when the aircraft is unfamiliar). In Figure 3, the current speed of the unknown aircraft designator is 325 knots. A commercial AID would predict speed capabilities ranging from 325 to 500 knots, suggesting that the aircraft was cruising well below maximum. On the other hand, a general aviation AID would indicate the aircraft was operating at top speed.

The availability of information inherent to both proposed models brings up an important point. Aircraft mix has been proposed as a traffic-related sector complexity factor. In other words, controllers have attributed their perceptions of increased workload to

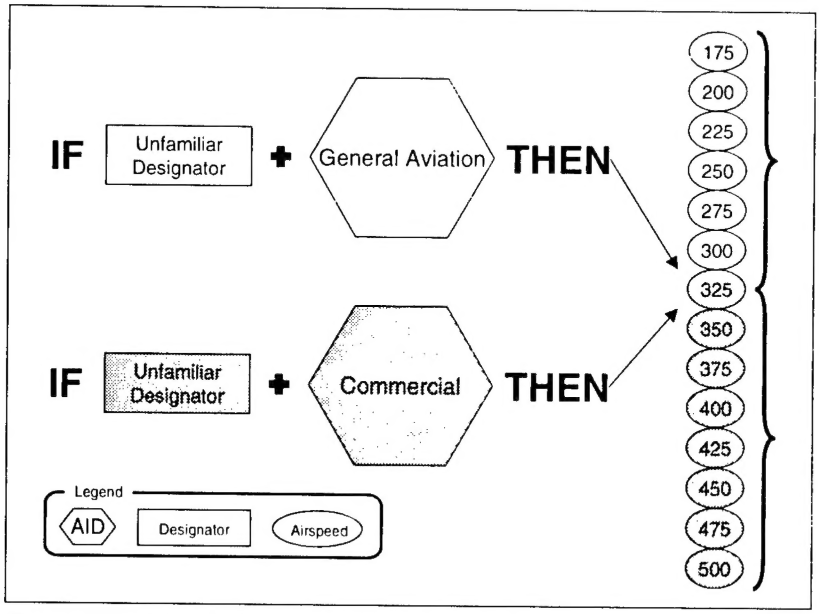

Figure 3. Model of Aircraft Performance Prediction When the Designator is Unfamiliar

"aircraft mix," which they believe to be characteristic of certain sectors. However, humans tend to confuse inference with observation (e.g., Brown, Deffenbacher, & Sturgill, 1977). It is doubtful that controllers are aware of all the factors contributing to their subjective experience. It is possible that one of the components of aircraft mix involves inadequate or inefficient cues for the prediction of aircraft performance. Controllers might be using information derived from a number of sources to estimate the true predictors of performance (e.g., engine number, engine type, weight class) to which they have no direct access. Workload in complex tasks has been related to the number of information sources and the number of cues (Proctor & Dutta, 1995). Inadequacies of prediction cues, or increased workload due to multiple information sources, might only be detectable under conditions in which the strain on the system exceeded a threshold; as would be the case in a low altitude sector with numerous aircraft of unknown performance characteristics.

By presenting only aircraft designators as stimuli, it should be possible to evaluate the effectiveness of the designator as a retrieval cue for aircraft performance estimates (i.e., average speed, climb, and descent rates). These estimates may then be employed to examine controllers' perceptions of each aircraft's performance capabilities relative to other aircraft in the sample by using multidimensional scaling (MDS) analysis. MDS translates patterns of responding into patterns of elements in a dimensional space. These patterns should provide evidence of knowledge-based prototypes. If prototypes are based on aircraft performance, adherence to the commercial, military, and private classifications would be subject to a considerable number of exceptions. This would be particularly true for aircraft that are encountered frequently because knowledge of exceptions to rules is gained through experience. In summation, while the subtleties of graded membership and fuzzy boundaries characteristic of prototype-based groups would be lost by asking controllers directly to classify aircraft, the nuances of the underlying dimensions governing controllers' perceptions might be revealed through the use of multidimensional scaling.

METHOD

Participants

Thirty en route air traffic control specialists participated in the study. All were full performance level (FPL) controllers meeting currency requirements. Six were in Oklahoma City as participants for an Air Traffic Selection and Training (AT-SAT) test validation study conducted by the FAA. Additional data were provided by specialists from the Boston ($N = 7$) and Kansas City ($N = 17$) Air Route Traffic Control Centers. Volunteers were treated according to guidelines established by the American Psychological Association. All were assured complete anonymity and reminded of their right to terminate participation at any time.

Six women and 24 men participated in the study. The mean age of participants was 40 with a standard deviation of 6 years, 4 months. As shown in Table 1, specialists had been at their current centers an average of 11 years, 10 months and had been certified as FPL controllers for an average of 9 years, 8 months. Discrepancies between the number of years as an en route FPL controller versus number of years as an air traffic control specialist represent time spent in training, in other areas, or at other facilities.

It was important for participants to have experience with the different altitude levels because the limitations of some propeller-driven aircraft preclude flight at higher altitudes. Of the 25 specialists who responded to items pertaining to sector stratification, 100% had worked high sector strata, 96% had worked low altitude, and 80% had worked ultra-high sectors. Though most acquired their experience at a single center, one specialist had worked at two centers, and another at three. The number of centers represented by participants was crucial for the generalizability of the results. Air Route Traffic Control Centers and the number of responses associated with each are listed in Table 2. These centers constitute 40% of the ARTCCs in the continental United States.

Table 1

*Summary of Participants' Professional Experience**

Amount of Time	Mean		*SD*		Minimum		Maximum	
	Yrs.	Mos.	Yrs.	Mos.	Yrs.	Mos.	Yrs.	Mos.
In Current Area	9	1	5	4	0	1	25	0
At Current ARTCC	11	10	4	8	1	9	25	0
As En Route FPL	9	8	4	8	0	7	23	0
As ATCS	15	2	6	9	3	4	35	0

* Summary statistics were calculated in months and converted to years/months.

Table 2

Air Route Traffic Control Center Experience

Air Route Traffic Control Center	Number of Responses ($N = 30$)
Albuquerque	3
Atlanta	1
Boston	7
Houston	2
Jacksonville	1
Kansas City	17
Miami	1
New York	1
Total Responses	33

Materials

The Aircraft Familiarity Questionnaire (AFQ). The AFQ is composed of 210 questions (excluding comments) that can be completed in 30-45 minutes. The questionnaire is divided into two sections: Aircraft Performance Characteristics and Familiarity.

In the Aircraft Performance Characteristics section of the AFQ, controllers were asked to supply speed, climb rate, descent rate, weight class, engine number, and engine type estimates for each of 30 aircraft. Space was also provided for comments regarding turn rate, limitations due to inclement weather, or any other performance-related information participants might have wished to add.

In the Familiarity section, volunteers were asked to estimate the frequency with which they had encountered the aircraft within the previous six months. Aircraft never or very rarely seen were to be classified Level 1. Aircraft were to be classified as Level 2 if the controller might not have seen one for several days, or if aircraft of this type are only found in certain sectors. Aircraft encountered daily in virtually all sectors were to be classified Level 3. A sample copy of the AFQ is provided in Appendix A.

AFQ aircraft list selection. The AFQ comprises 30 aircraft drawn from an initial pool of 403 designators extracted from the aircraft characteristics record of New York Center's (ZNY) Adaptation Control Environment System (ACES) tape. For the 30 aircraft in the AFQ to be truly representative, it was important to begin with a list of aircraft that might be encountered in any given airspace. Therefore, the New York list was compared with aircraft characteristics records from the Los Angeles (ZLA) and Cleveland (ZOB) centers. All three records were relatively recent updates, ranging from June 1996 (ZLA) to January 1998 (ZNY). Only designators found in all three lists were retained. Further reduction of the remaining 314 aircraft types was accomplished in two phases. Phase 1 elimination addressed the availability of information and the distinctiveness of the stimuli. Phase 2 focused on maintaining a balance of commercial, military, and private aircraft, while ensuring that some aircraft in the sample would be less familiar than others. In other words, Phase 2 was about diversity and variability.

As shown in Table 3, most Phase 1 deletions were due to lack of inclusion in Appendix A of the 7110.65L. The 7110.65L is the most recent version of the air traffic control manual (FAA, 1998). Therefore, all air traffic control specialists would have access to this information. This would not be true of aircraft not listed in the 7110.65L. Multiple designators and "cross-designators" (i.e., designators that have been reassigned) were also eliminated to avoid stimulus ambiguity. For example, in the recent adoption of new designators aircraft with old designators C135, KC35, KE35, and KR35 were grouped under the new designator C135. Conversely, an aircraft previously designated as T35 were assigned to either the new designator PILL or PA28.

Phase 2 list reduction began with a search of log reports generated by the National Airspace System (NAS) Data Analysis and Reduction Tool (DART). Log reports contain the aircraft identifier and type of every aircraft crossing a given airspace. A 20-minute sample of the July 1996 log report from the New York ARTCC was examined for the incidence of AIDs corresponding to the 148 aircraft types remaining after Phase 1 deletions. There were 14 aircraft types

Table 3

Phase 1 List Reduction: Frequencies and Exclusion Criteria

A/C Deleted	Exclusion Criteria
82	Not in the 7110.65L
64	Multiple Old Designators/ One New Designator
8	Multiple New Designators/ One Old Designator
4	"Cross-Designators"
7	Redundancies (Both Old and New Designators)
1	Test Dummy
166	Total Deletions

detected more than once within the 20 minutes sampled (e.g., more than one B757 crossed the airspace). In that same time frame, 41 of the aircraft types appeared only once or twice. The 93 aircraft types that did not appear in the New York log report were excluded from further consideration.

The next step involved examination of the July 1996 log report from the Atlanta ARTCC to determine the frequency of occurrence of the 55 remaining aircraft types. The sample time frame was extended to 30 minutes to ensure that a sufficient number of aircraft would be selected. Ten of the 14 designators with multiple occurrences in the New York log report were also detected more than once in Atlanta's airspace. These ten designators, representing frequently-encountered aircraft, were included in the final list. Ten of the 17 general aviation aircraft that had been detected only once or twice in the 20-minute New York sample were retained for the final list by randomly sorting them and selecting the first ten. Ten military aircraft, also with minimal frequency of occurrence, were selected via the same process.

Aircraft Familiarity Data Analysis Tool (AFDAT). Completed AFQ forms were transferred to an electronic format using the AFDAT, a Visual Basic program developed to facilitate data entry and guard against error. For example, two versions of the AFQ, which differed in the order in which the aircraft were presented, were given to participants. The AFDAT "Version" option allows for items to be entered according to version order, and automatically sorts the aircraft alphabetically for output. AFDAT code also prohibits entry of any number outside the possible range of values for categorical variables.

Evaluation of weight class, engine number, and engine type responses are performed automatically by AFDAT code, thereby eliminating the possibility of scoring errors. In addition, the AFDAT generates a categorical variable describing the exact nature of the error (e.g., a turboprop mistaken for a jet, a piston mistaken for a turboprop) when an incorrect engine type response is detected. The AFDAT returns a single speed, climb, and descent rate for each aircraft. When two values are entered (e.g., a range of speed capabilities), AFDAT code automatically computes a mean estimate.

Design

Multidimensional scaling refers to a group of descriptive procedures that transform data into mapped elements in one or more spatial dimensions (Kruskal & Wish, 1978). Theoretically, the configuration describes the underlying dimensions upon which judgments were based. The appropriate data for MDS analysis are proximities, numbers that indicate the similarity or dissimilarity of a set of objects. Proximities may be obtained directly, or derived mathematically from a set of variables. In this application, a single matrix of dissimilarity measures was computed from summary estimates of performance characteristics (i.e., mean speed, climb, and descent rates). The squared Euclidean distance between vectors of estimates was computed for each aircraft. The distances, therefore, represent composite measures of controllers' perceptions of each aircraft's capabilities relative to other aircraft in the sample. For example, if summary estimates for the first and second aircraft were:

	Speed	Climb	Descent
Aircraft 1	1	2	3
Aircraft 2	4	5	6

The squared Euclidean distance for these aircraft would be: $(1\text{-}4)^2 + (2\text{-}5)^2 + (3\text{-}6)^2 = 27$ (D. Nichols, personal communication, November 18, 1998).

Aircraft sample size was evaluated prior to data collection, and the number of aircraft was limited to 30 so that the time required to complete the questionnaire remained under one hour. Early in the planning stages, it was understood that volunteers would be donating their time and expertise gratis, and it was considered to be unreasonable to request any more than 30 to 45 minutes of time.

In addition to performance estimates, participants were asked to provide information regarding a number of variables to be used for interpretation of the MDS model (i.e., engine number, engine type, and weight class). Tests of accuracy for these variables might also prove highly informative. Estimates of frequency of encounter for each aircraft were collected as well. Research has shown that humans are relatively accurate with such judgments (Vlek, 1970; as cited in Tversky & Kahneman, 1973). These

"familiarity ratings" were used in the multiple regression interpretation of the stimulus configuration and to assess controllers' certainty regarding all other estimates.

Procedure

For the six participants drawn from the AT-SAT pool, testing was conducted at the Assessment Center located on the grounds of the Mike Monroney Aeronautical Center in Oklahoma City, Oklahoma. Testing took place from April 1 to 23, 1998, after participants had completed the AT-SAT experimental protocol. The 15% who volunteered to remain and take the AFQ were given consent forms to read and sign. Once written consent had been obtained, packets were distributed. Packets consisted of biographical data forms, instructions, and one of two versions of the AFQ. As soon as the questionnaires were finished, the specialists were debriefed.

Data collection at the Boston and Kansas City ARTCCs took place between April 28 and May 24, 1998. Volunteers meeting subject criteria were solicited by a representative from each center. Both representatives had been thoroughly briefed on important points of procedure, particularly with regard to obtaining written consent prior to dispensing the packets. Though test administration at the centers was somewhat less formal, the basic experimental protocol remained unaltered.

RESULTS

Data Management

Text files generated by the AFDAT program were aggregated to create a new data file. Observations in the aggregated file represent summary APC scores (weight class, engine number, engine type) and performance estimates (speed, climb, and descent) for each aircraft. Prior to aggregation, distributions of performance estimates were examined separately for each of the 30 aircraft in the AFQ. Departures of skewness and kurtosis for all 180 distributions (90 scores, 90 estimates) were reduced to a maximum of 3.36 (skewness) and 3.38 (kurtosis) standard deviations from that expected of a normal distribution (see Tabachnik & Fidell, 1989, p. 72) by the removal of outliers and extreme values (see SPSS Inc., 1990, p. 174 for criteria). After deletion, tests of normality indicated the mean was a sufficient measure of central tendency for all observations. Summary observations and the number of cases they were based upon are listed in Appendix B. Observations with $N < 30$ resulted from missing values, deletion, or both.

Missing Values

Controller characteristics. The total number of missing values was computed for each participant. This variable was compared with biographical information stored in the BIODAT data file generated by the AFDAT program. The distributions of chronological age (in years), time spent as an air traffic controller (in months), and total number of missing values approximated normality in terms of skewness and kurtosis. The Pearson product-moment correlation coefficient (N = 29) found no reliable linear relationship between missing values and chronological age (r = .12), or time spent as an air traffic controller (r = .10).

Aircraft characteristics. The total number of missing values was computed for all variables and compiled by aircraft designator. This summary variable was merged with the existing AFDAT data base for comparison with APC measures. The distribution of mean Familiarity ratings sufficiently approximated normality for parametric analysis; the distribution of total missing values did not. Departures of skewness (Skewness = 2.23; S.E. Skewness = .43) and kurtosis (Kurtosis = 4.59; S.E. Kurtosis = .83) were improved with a square root transformation (Skewness = 1.38; Kurtosis = 1.33). Nevertheless, a considerable number of outliers remained. Sample size contraindicated deletion of cases, so Spearman's correlation coefficient for ranked data was selected as the appropriate measure of association. Ranking invariably results in a loss of information, with a subsequent loss of power. A relatively small sample size (N = 30) further increased the risk of a Type II error. In spite of that, ranks of total missing values demonstrated a significant inverse relationship with those of mean Familiarity ratings (r_s = -.65, $p < .01$). Missing values demonstrated a reliable positive association with the percentage of incorrect engine type responses (r_s = .60, $p < .01$), but not with other APC measures. As might be expected, mean Familiarity ratings and incorrect engine type responses were significantly and negatively related (r_s = -.52, $p < .01$).

Multidimensional Scaling

Squared Euclidean distances were calculated from standardized speed, climb, and descent rate summary estimates and submitted to classical, nonmetric MDS analysis. Both two- and three-dimensional models demonstrated excellent fit. Squared correlations describe the relationship between the original distances and the derived stimulus coordinates: Both solutions produced an $r^2 = .99$. Kruskal's stress 1 formula is sometimes referred to as a "badness-of-fit" measure because larger values indicate poorer fit. The two- and three-dimensional solutions yielded stress values of .0098 and .0078, respectively. In the best of all possible models, stress equals zero.

Selection of the appropriate dimensionality concentrated on issues of parsimony and interpretability. Intercorrelations of stimulus coordinates in Table 4 reveal that Dimension 1 remained stable ($r = 1.00$) regardless of dimensionality. Dimension 2 was relatively unchanged as well ($r = -.97$). Examination of stimulus coordinates and regression analysis failed to uncover any distinctive, interpretable features of the added dimension. Because a higher dimensionality is of little use if it contributes nothing to the interpretation of the solution (Kruskal & Wish, 1978), two dimensions were deemed sufficient.

The most objective technique available for dimensional interpretation is the regression method. Variables believed to correspond with the stimulus configuration are regressed on vectors of coordinates. According to Kruskal and Wish (1978), two conditions are necessary for satisfactory interpretation of a dimension. First, the multiple correlation must be extremely high (correlations in the .90s are recommended, although correlations in the .70s will suffice). As shown in Table 5, only engine type ($R = .92$) and weight class ($R = .80$) achieved the recommended degree of association with the dimensions. The percentage of incorrect engine type responses produced an $R = .65$. Although the magnitude of this association is less than the recommended level, significance exceeds the minimum requirement of .01 (Kruskal & Wish, 1978, p. 39).

Table 4

Intercorrelations of Multidimensional Scaling Model Stimulus Coordinates for Two- and Three-Dimensional Solutions (N = 30)

Dimension	1	2	3	4	5
1 Dimension1 (of Two)	—	.05	1.00*	.16	-.21
2 Dimension 2 (of Two)		—	.07	-.97*	-.75*
3 Dimension 1 (of Three)			—	.15	-.22
4 Dimension 2 (of Three)				—	.65*
5 Dimension 3 (of Three)					—

* Correlation is significant at $p < .01$ level (2-tailed).

Table 5

Summary of Multiple Regression Analyses Used to Interpret Dimensional Characteristics of the Two-Dimensional MDS Model [a]

Criterion	R	R^2	F	p	β_1	β_2
Engine Number	.51	.26	4.65	.02	-.11	.50
Percent Incorrect: Engine Number	.26	.07	.99	.38	-.24	-.10
Engine Type	**.92**	.85	78.12	**.000**	**-.84**	.43
Percent Incorrect: Engine Type	**.65**	.42	9.75	**.001**	**.62**	-.22
Weight Class	**.80**	.63	22.59	**.000**	-.41	**.70**
Percent Incorrect: Weight Class	.24	.06	.81	.45	-.23	-.05
AFQ Familiarity Rating	.37	.13	2.08	.15	-.02	.37
Square Root of Total Missing	.37	.14	2.17	.13	.28	-.26

[a] Bold items represent significant associations.

The second condition required for a satisfactory interpretation is that the criterion must have a high regression weight on the dimension. Standardized regression weights show that Dimension 1 was related to engine type (β_1 = -.84) and the percentage of incorrect engine type responses (β_1 = .62), whereas Dimension 2 was associated with weight class (β_2 = .70). Table 6 contains a list of aircraft designators ordered by Dimension 1 coordinates. The relationship between engine type and the arrangement of elements along this dimension is evident. The association between modal engine type and mean speed estimates (r_s = .86, p < .01) is also apparent. Notice that the proportion of errors increases around "fuzzy boundaries" of engine type estimates.

Table 7 provides information about the exact nature of engine type errors. Most errors (60%) involved confusion between turboprops and piston-driven aircraft. Specialists were nearly twice as likely to mistake a turboprop for a jet than to mistake a piston-driven aircraft for a jet. Participants were least prone to mistake a jet for any other kind of aircraft.

Table 6

Aircraft Type Designators, Engine Type Estimates, Percentage of Engine Type Estimates Incorrect, and Speed Estimates Ordered by Dimension 1 Coordinates

Designator	Engine Type	Percent Incorrect	Speed Estimate
C208	Piston	62%	177
BE36	Piston	7%	163
BE58	Piston	20%	191
AC50	Piston	47%	196
PA46	Piston	41%	203
V10	Turboprop	48%	224
E120	Turboprop	14%	258
SF34	Turboprop	7%	253
C2	Turboprop/Jet *	64%	320
D328	Turboprop	25%	272
JSTB	Turboprop	39%	305
C97	Turboprop	75%	376
C560	Jet	3%	393
MD80	Jet	0%	453
C141	Jet	10%	450
B52	Jet	3%	475
A3	Jet	19%	377
L101	Jet	3%	492
MD11	Jet	0%	478
A310	Jet	0%	461
A300	Jet	0%	465
A320	Jet	0%	472
B757	Jet	0%	474
B767	Jet	0%	480
C650	Jet	0%	472
LJ55	Jet	0%	464
HAR	Jet	0%	473
F111	Jet	0%	500
F16	Jet	0%	500
T38	Jet	0%	488

* Bimodal

Table 7

Frequencies and Percentages of Specific Engine Type Errors

Description of Error	Frequency	Percent
Turboprop Mistaken for Piston	35	30
Piston Mistaken for Turboprop	34	30
Turboprop Mistaken for Jet	23	20
Piston Mistaken for Jet	14	12
Jet Mistaken for Turboprop	6	5
Jet Mistaken for Piston	3	3
Total	115	100

The relationship between weight class and Dimension 2 was not as straightforward as that of engine type and Dimension 1. Estimates of weight class were related to those of climb rates ($r_s = .40$) and descent rates ($r_s = .41$) at the $p < .05$ level of significance, but weight classes were not evenly distributed along a continuous dimension. Table 8 contains a list of aircraft ordered by Dimension 2 coordinates, separated according to their position in the four quadrants of the stimulus configuration map (see Figure 4). Organized in this manner, at least three distinct groups emerge: (a) heavy and large jet aircraft with climb and descent capabilities greater than 2100 feet per minute (fpm) but less than 3000 fpm, and average cruising speeds greater than 450 knots,(b) small turboprops and pistons with slower cruising speeds and somewhat limited climb and descent capabilities, and (c) high-performance jets.

DISCUSSION

Visual examination of the stimulus configuration map, shown in Figure 4, reveals three clusters of aircraft. At first glance, these groups appear to correspond to commercial, military, and private classifications. For instance, aircraft in the upper-left region are predominantly commercial air carriers. The lower-left area consists primarily of military aircraft, whereas general aviation aircraft dominate the lower-right quadrant. Upon closer examination, however, the perception of discrete categories must be dismissed. By definition, categories have boundaries, and all elements within the boundary belong equally to the group (Schwartz & Reisberg, 1991). Therefore, a categorical interpretation cannot account for the small cluster of three aircraft in the upper-right quadrant. Neither can it explain the presence of civil aircraft in the lower-left area, nor the number of military aircraft scattered throughout the configuration. Clearly then, a strict categorical interpretation is insufficient.

One solution may be prototype-based categories, as described by Schwartz and Reisberg (1991), that are not absolute. Prototypes are characterized by graded membership and fuzzy boundaries. That is, some members of the group are more representative of the prototype than others. The systematic progression of participants' speed estimates along Dimension 1, shown in Table 6, is typical of the graded membership often associated with prototypes. Ranges of climb and descent rates, shown in Table 8, also suggest graded membership.

The position of the C650 and LJ55 in the stimulus configuration suggests graded membership as well. Speed estimates of the C650 and LJ55 were similar to other high-performance aircraft, though not to the same degree as military jets situated in the far left corner of the configuration. Participants' speed estimates for these aircraft were comparable to manufacturers' published cruising speeds. In addition, speed estimates for these aircraft had below-average standard deviations. However, it should be noted that modal weight class estimates for the C650 and LJ55 were incorrect: Estimated to be Large aircraft, both are actually in the Small weight class category. Some participants greatly underestimated the climb and descent capabilities of these aircraft, resulting in standard deviations that were high, as compared with

Table 8

Aircraft Type Designators, Estimates of Engine Type,• Weight Class,✦ Speed, Climb and Descent Rates, Ordered by Dimension 2 Coordinates

Designator	Engine/ Weight	Speed	Climb	Descent	Designator	Engine/ Weight	Speed	Climb	Descent
L101	J H	492	2284	2836					
B52	J H	475	2180	2341					
MD11	J H	478	2478	2583					
MD80	J L	453	2144	2315					
C141	J H	450	2320	2204					
A320	J H	472	2714	2530					
A300	J L	465	2580	2542					
A310	J L	461	2496	2665					
B767	J H	480	2893	2807					
B757	J H	474	2915	2738					
					C560	J L	393	1985	2160
					C2	T L	320	1628	1522
					C97	T H	376	1892	2103
C650	J L	472	3148	3166					
					E120	T L	258	1347	1654
					C208	P S	177	981	1010
					PA46	T S	203	1180	1265
					V10	T S	224	1412	1425
					BE36	P S	163	1006	1193
					BE58	P S	191	1096	1250
					AC50	P S	196	1128	1309
LJ55	J L	464	3502	3633					
					SF34	T L	253	1673	1615
					JSTB	T L	305	2052	2150
					D328	T L	272	1897	1847
F111	J L	500	4005	4540					
A3	J L	377	2989	2627					
HAR	J L	473	3961	4221					
F16	J L	500	4685	5333					
T38	J S	488	5007	5280					

• J = Jet, T = Turboprop, P = Piston; ✦ H = Heavy, L = Large, S = Small

the rest of the sample. It is possible that the position of the C650 and LJ55 might have been closer to other high-performance jets, had participants been aware of their actual weight class.

Because prototypes are abstracted from stored information, they will generally accommodate exceptions (Posner, Goldsmith, & Welton, 1967). The proximity of the C650 and LJ55 to military aircraft such as the F111 and F16 demonstrates this phenomenon to some degree. Even more dramatic is the appearance of military aircraft (i.e., the B52 and C141) within the tightly-knit cluster of commercial air carriers in the upper-left area of the configuration. Controllers' speed, climb, and descent rate estimates for the B52 and C141 were within the same range as other performance estimates in the group. According to the manufacturers' published averages, their estimates were extremely accurate. Thus, these civil and military aircraft were related by performance characteristics.

Although prototypes allow for recognition of elements that are unusual, research involving pattern recognition has demonstrated that well-learned forms do not accommodate as wide a range of distortion as less familiar ones (e.g., Petersen, Meagher, Chait, and Gillie, 1973). Most controlled aircraft are commercial jets. If controllers develop prototypes, the commercial jet would be analogous to a well-learned form, much as a triangle or a circle would be in pattern recognition. One of the most distinctive

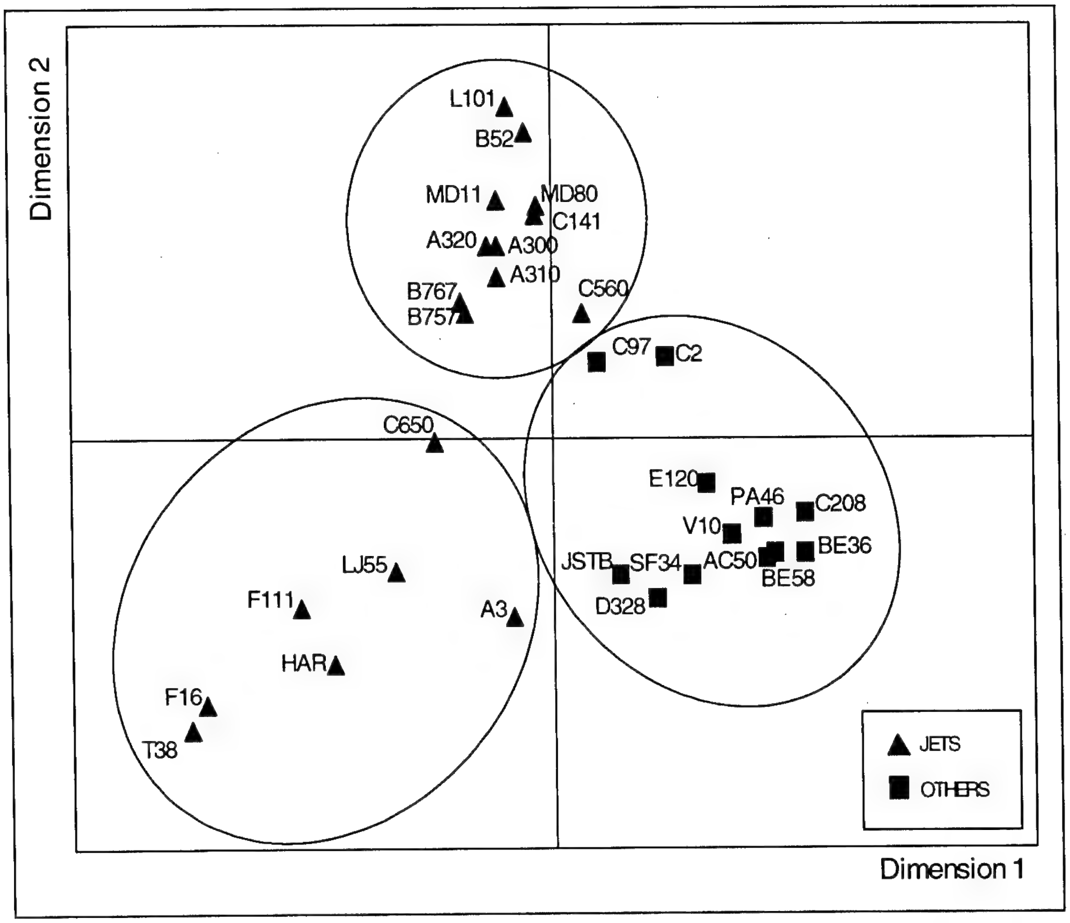

Figure 4. Derived Stimulus Configuration of the Two-Dimensional MDS Model

features of the stimulus configuration map is the nearly inviolable line separating jets and other aircraft. The only exception is the C560, Cessna Citation, a notoriously slow jet aircraft. According to self-report estimates, controllers were extremely familiar with this aircraft. Of a possible 2.00, the C560 had a mean Familiarity rating of 1.90. As might be expected, performance estimates for the C560 were fairly accurate. Therefore, it is likely that the C560 is proximal to turboprops and pistons because it does not perform within the same parameters as other jet aircraft. (As one controller stated, "The Citation is really a turboprop masquerading as a jet.") Thus, the Citation's placement in the configuration may be attributed to excessive distortion of a well-learned form (i.e., the commercial jet).

Characteristics of the configuration indicate that controllers may develop prototype-based categories of aircraft, while interpretation of the multidimensional scaling dimensions suggests that the exemplars of these prototypes are performance-based. Multiple regression interpretation revealed a strong relationship between Dimension 1 and engine type. However, this relationship does not appear to describe a simple "jets, turboprops, pistons" delineation. As mentioned previously, one of the most striking features of the configuration is the line of demarcation between jets, to the left, and all other aircraft types. Two distinct groups of jet aircraft are distinguishable in the stimulus configuration: Jets with climb and descent capabilities ranging from approximately 2200 to 3000 fpm, and high-performance jets with climb and descent capabilities greater than 3000 fpm. The third group comprises propeller-driven aircraft with climb and descent capabilities ranging from approximately 1000 to 2150 fpm. Two subgroups consisting of pistons and turboprops, barely visible in the stimulus configuration, are readily apparent in Table 6. These subgroups are separated by fuzzy boundaries, evidenced by patterns of engine type errors. The

nature of these errors, shown in Table 7, indicates that this "fuzziness" may be due to a lack of discriminability between the performance capabilities of turboprops and pistons. Apparently, propeller-driven aircraft are perceived as being more alike than different.

The model of prototype development in Figure 2 proposes that controllers develop expectations regarding aircraft performance based on repeated pairings of aircraft designators and current speeds. Notably however, the significant inverse relationship between Familiarity and missing values indicates that the designator was an ineffective cue for the retrieval of performance characteristics when estimated frequency of encounter was low. Furthermore, aircraft with extremely low Familiarity ratings were not strongly associated with any group. The uncertainty represented by the position of these elements in the configuration also demonstrates the inadequacy of the designator as a sufficient cue. For example, the A3 Skywarrior "floats" to the right of other high-performance military aircraft. The Skywarrior had the lowest Familiarity rating in the sample (.03) and one of the highest incidences of missing values. Standard deviations for all three performance estimates were notably high for this aircraft (see Appendix B). Contrary to participants' average perception of 377 knots, the Skywarrior's published long-range cruising speed is approximately 450 knots. Individual speed estimates for this aircraft fluctuated widely, ranging from as low as 160 knots to as high as 550 knots. Variability in estimated climb and descent rates were similarly erratic. Estimates ranged from 750 fpm to a notably accurate 6000 fpm.

The positions of the C2 and C97, located near the C560 in the upper-right area of the configuration, also appear to be due to uncertainty. Like the A3, the C2 and C97 had very low Familiarity ratings (.14 and .27, respectively). Furthermore, a considerable number of missing values was associated with both aircraft (see Appendix B). The C2 engine type estimate was bimodal. Approximately half of the participants thought the C2 might be a jet, while others accurately estimated the aircraft to be a turboprop. (The remainder guessed that the aircraft was piston-driven.) Participants' mean speed estimate for the C2 was 320 knots, although the maximum speed of this aircraft is listed as only 300 knots. Participants (75%) inaccurately estimated the C97 to be a turboprop. The C97 is actually a piston-driven aircraft. Participants estimated the average speed of the C97 to be 376 knots. The published average cruising speed of this aircraft is 200 knots, and its maximum speed is only 350 knots. Standard deviations of speed estimates for both the C2 and C97 were higher than average as well. The average standard deviation for all speed estimates was approximately 48 knots. The standard deviations for these two aircraft were 113 knots (C2) and 103 knots (C97). Climb and descent rate estimates demonstrated similar attributes.

It seems likely that the position of the C2 and C97 in the configuration reflects an average between inaccurately high estimates of performance and those characteristic of aircraft in the lower-right quadrant. Individual performance estimates appeared to be based on assumptions regarding the engine type of the aircraft. Participants who correctly estimated the aircraft's engine type were also more accurate in their performance estimates. The strength of the positive association between missing values and incorrect engine type responses, in conjunction with the inverse relationship between missing values and Familiarity ratings, suggests that repeated exposure may increase the precision of engine type estimates. Patterns of responding associated with the C2 and C97 indicate that the accuracy of engine type estimates may have a direct impact on the prediction of an aircraft's performance capabilities.

CONCLUSIONS

In the aggregate, the results of the analysis are compelling evidence supporting further investigation into the efficacy of display cues for prediction of aircraft performance. It is interesting to note that controllers appear to have developed prototypes corresponding to information that is not readily available to them. This implies that prototypes might have been developed using multiple cues (i.e., AID, designator, current speed) obtained from a number of sources (i.e., datablock, flight progress strip, flight plan readout). Although the accuracy with which participants estimated the capabilities of familiar aircraft indicates that controllers have managed to overcome the inadequacies of available cues, patterns of responding associated with unfamiliar aircraft suggest that this knowledge might have been purchased at a greater cost than necessary.

It has been demonstrated that workload in complex tasks is related to the number of information sources, and the number of cues (Proctor & Dutta, 1995). It logically follows that workload might be

reduced by providing more effective cues from a single source. Results of multiple regression interpretation of the dimensions underlying controllers' perceptions of aircraft groups suggest that the use of engine type and weight class might be beneficial. For example, a Heavy jet aircraft might be accompanied by an "HJ" on the datablock tag, proximal to the AID. The effects of these indicators could be tested in a simulated environment using control and experimental groups to compare subjective measures of workload and objective measures of performance associated with each condition. It is possible that enhancement of prediction cues, similar to the one suggested, might increase the efficiency of controllers' decision making and decrease perceived workload, particularly in sectors with a high ratio of unfamiliar vs. familiar aircraft.

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APPENDIX A

Aircraft Familiarity Questionnaire (AFQ)

1) At how many En route Centers have you worked? ____________ (number of centers)
Please list the centers you have worked at, beginning with the most recent:

1) ______________________________
2) ______________________________
3) ______________________________
4) ______________________________

2) How long have you worked in your current area?
__________ years __________ months

3) How long have you worked at your current ARTCC?
__________ years __________ months

4) How many years and months (total) have you worked at an En Route Center as an FPL?
__________ years __________ months

5) Please indicate your total number of years as a controller.
__________ years __________ months

6) Please indicate all operations in which you have been an FPL (check all that apply)
__________ En Route
____ Low
____ High
____ Ultra High
__________ Terminal
__________ Flight Service Station
__________ Other

7) When were you last certified or re-certified?
__________ (year)

OPTIONAL:

1) Age _________
2) Gender _________

Instructions

The suggested strategy for both sections of the questionnaire is to "fly" through the aircraft types. Do not deliberate too long over your responses. Your initial response will probably be the most accurate.

Section 1: Familiarity

"Familiarity" is defined as the frequency with which you might encounter a particular aircraft in your airspace. For example, some controllers encounter a great deal of military or general aviation aircraft and are relatively familiar with them. These same aircraft might be unfamiliar to a specialist working a sector that generally handles commercial flights only. Level 1 aircraft are those you rarely or never see. If you might not come across a particular aircraft type for several days, or only when working certain sectors, that aircraft should be classified as Level 2. Aircraft types encountered daily in virtually all sectors are Level 3 aircraft. Simply mark the box corresponding to the level that best describes the frequency with which you have encountered each aircraft type over the past six months.

Section 2: Aircraft Performance Characteristics

Weight Class: Please choose from one of three basic weight classes: Heavy (H), Large (L), or Small (S).

Speed: Please provide an approximate range of performance capabilities. (For example, a B737 generally cruises somewhere between 400 and 470 knots). It is not necessary to indicate whether your answer is expressed in Mach speed or knots, but feel free to circle the appropriate indicator located to the right of the answer blank.

Climb Rate / Descent Rate: It is anticipated that you will possess general knowledge of aircraft climb and descent capabilities. If your answer is an average climb or descent rate, simply write a single value in the space. If you think of climb and descent rates in ranges, then write the range in the space provided. If you think only in terms of maximums, then write the value in the space and be sure to indicate that it is a maximum rate rather than an average.

Engines:

Type: Please choose from one of three basic engine types. The following abbreviations are provided only for your convenience. If you prefer, ignore the suggested abbreviations and write "piston" or "turboprop" or "jet."

- **P** = reciprocating, or piston-driven
- **T** = turboprop
- **J** = turbojet

Number: If you are unsure, give it your best guess.

Comments: Please write information regarding the aircraft's turn rate, limitations due to inclement weather, or other performance-related information in the space provided.

SECTION 1: FAMILIARITY

Please check the box that corresponds to the level that best describes the frequency with which you have encountered each aircraft type over the past 6 months:

Level 1: Aircraft rarely or never seen.
Level 2: Aircraft you might not come across for several days, or only encounter when working certain sectors.
Level 3: Aircraft types encountered daily in virtually all sectors.

	Old Designator	New Designator	Level 1	Level 2	Level 3
1	LR55	LJ55	☐	☐	☐
2	A3	A3	☐	☐	☐
3	C208	C208	☐	☐	☐
4	T38	T38	☐	☐	☐
5	AV8	HAR	☐	☐	☐
6	KC97	C97	☐	☐	☐
7	BA41	JSTB	☐	☐	☐
8	EA31	A310	☐	☐	☐
9	SF34	SF34	☐	☐	☐
10	D328	D328	☐	☐	☐
11	BE36	BE36	☐	☐	☐
12	F111	F111	☐	☐	☐
13	PA46	PA46	☐	☐	☐
14	C560	C560	☐	☐	☐
15	EA30	A300	☐	☐	☐
16	BE58	BE58	☐	☐	☐
17	MD11	MD11	☐	☐	☐
18	MDD8	MD80	☐	☐	☐
19	OV10	V10	☐	☐	☐
20	C2	C2	☐	☐	☐
21	B767	B767	☐	☐	☐
22	AC50	AC50	☐	☐	☐
23	B52	B52	☐	☐	☐
24	EA32	A320	☐	☐	☐
25	B757	B757	☐	☐	☐
26	C650	C650	☐	☐	☐
27	E120	E120	☐	☐	☐
28	L101	L101	☐	☐	☐
29	C141	C141	☐	☐	☐
30	F16	F16	☐	☐	☐

SECTION 2: AIRCRAFT PERFORMANCE CHARACTERISTICS

1 Old Designator E120 New Designator E120
Weight Class: ________
Climb Rate: _____________ fpm
Speed: ______________kts M
Descent Rate: ___________ fpm
Engines:
Number ________
Type ___________

Comments: ____

2 Old Designator LR55 New Designator LJ55
Weight Class: ________
Climb Rate: _____________ fpm
Speed: ______________kts M
Descent Rate: ___________ fpm
Engines:
Number ________
Type ___________

Comments: ____

3 Old Designator T38 New Designator T38
Weight Class: ________
Climb Rate: _____________ fpm
Speed: ______________kts M
Descent Rate: ___________ fpm
Engines:
Number ________
Type ___________

Comments: ____

4 Old Designator OV10 New Designator V10
Weight Class: ________
Climb Rate: _____________ fpm
Speed: ______________kts M
Descent Rate: ___________ fpm
Engines:
Number ________
Type ___________

Comments: ____

5 Old Designator L101 — New Designator L101

Weight Class: ________
Climb Rate: ______________ fpm
Speed: _______________kts M
Descent Rate: ____________ fpm
Engines:
Number ________
Type ____________

Comments: ____

6 Old Designator BE58 — New Designator BE58

Weight Class: ________
Climb Rate: ______________ fpm
Speed: _______________kts M
Descent Rate: ____________ fpm
Engines:
Number ________
Type ____________

Comments: ____

7 Old Designator T38 — New Designator T38

Weight Class: ________
Climb Rate: ______________ fpm
Speed: _______________kts M
Descent Rate: ____________ fpm
Engines:
Number ________
Type ____________

Comments: ____

8 Old Designator B52 — New Designator B52

Weight Class: ________
Climb Rate: ______________ fpm
Speed: _______________kts M
Descent Rate: ____________ fpm
Engines:
Number ________
Type ____________

Comments: ____

9 Old Designator KC97 New Designator C97

Weight Class: ________
Climb Rate: _____________ fpm
Speed: ______________kts M
Descent Rate: ___________ fpm
Engines:
Number ________
Type ___________

Comments: ____

10 Old Designator C650 New Designator C650

Weight Class: ________
Climb Rate: _____________ fpm
Speed: ______________kts M
Descent Rate: ___________ fpm
Engines:
Number ________
Type ___________

Comments: ____

11 Old Designator AC50 New Designator AC50

Weight Class: ________
Climb Rate: _____________ fpm
Speed: ______________kts M
Descent Rate: ___________ fpm
Engines:
Number ________
Type ___________

Comments: ____

12 Old Designator BA41 New Designator JSTB

Weight Class: ________
Climb Rate: _____________ fpm
Speed: ______________kts M
Descent Rate: ___________ fpm
Engines:
Number ________
Type ___________

Comments: ____

13 Old Designator B757 New Designator B757

Weight Class: ________
Climb Rate: ______________ fpm
Speed: _______________kts M
Descent Rate: ____________ fpm
Engines:
Number ________
Type ____________

Comments: ____

14 Old Designator A3 New Designator A3

Weight Class: ________
Climb Rate: ______________ fpm
Speed: _______________kts M
Descent Rate: ____________ fpm
Engines:
Number ________
Type ____________

Comments: ____

15 Old Designator D328 New Designator D328

Weight Class: ________
Climb Rate: ______________ fpm
Speed: _______________kts M
Descent Rate: ____________ fpm
Engines:
Number ________
Type ____________

Comments: ____

16 Old Designator MD11 New Designator MD11

Weight Class: ________
Climb Rate: ______________ fpm
Speed: _______________kts M
Descent Rate: ____________ fpm
Engines:
Number ________
Type ____________

Comments: ____

17 Old Designator C208 New Designator C208

Weight Class: ________
Climb Rate: _____________ fpm
Speed: ______________kts M
Descent Rate: ___________ fpm
Engines:
Number ________
Type ___________

Comments: ____

18 Old Designator C2 New Designator C2

Weight Class: ________
Climb Rate: _____________ fpm
Speed: ______________kts M
Descent Rate: ___________ fpm
Engines:
Number ________
Type ___________

Comments: ____

19 Old Designator C560 New Designator C560

Weight Class: ________
Climb Rate: _____________ fpm
Speed: ______________kts M
Descent Rate: ___________ fpm
Engines:
Number ________
Type ___________

Comments: ____

20 Old Designator F16 New Designator F16

Weight Class: ________
Climb Rate: _____________ fpm
Speed: ______________kts M
Descent Rate: ___________ fpm
Engines:
Number ________
Type ___________

Comments: ____

21 Old Designator BE36 — New Designator BE36

Weight Class: ________
Climb Rate: ______________ fpm
Speed: _______________kts M
Descent Rate: ____________ fpm
Engines:
Number ________
Type ____________

Comments: ____

22 Old Designator EA30 — New Designator EA30

Weight Class: ________
Climb Rate: ______________ fpm
Speed: _______________kts M
Descent Rate: ____________ fpm
Engines:
Number ________
Type ____________

Comments: ____

23 Old Designator C141 — New Designator C141

Weight Class: ________
Climb Rate: ______________ fpm
Speed: _______________kts M
Descent Rate: ____________ fpm
Engines:
Number ________
Type ____________

Comments: ____

24 OOld Designato EA30 — New Designator A320

Weight Class: ________
Climb Rate: ______________ fpm
Speed: _______________kts M
Descent Rate: ____________ fpm
Engines:
Number ________
Type ____________

Comments: ____

25 Old Designator MD80 New Designator MD80

Weight Class: ________
Climb Rate: _____________ fpm
Speed: ______________kts M
Descent Rate: ___________ fpm
Engines:
Number ________
Type ___________

Comments: ____

26 Old Designator EA31 New Designator A310

Weight Class: ________
Climb Rate: _____________ fpm
Speed: ______________kts M
Descent Rate: ___________ fpm
Engines:
Number ________
Type ___________

Comments: ____

27 Old Designator F111 New Designator F111

Weight Class: ________
Climb Rate: _____________ fpm
Speed: ______________kts M
Descent Rate: ___________ fpm
Engines:
Number ________
Type ___________

Comments: ____

28 Old Designator PA46 New Designator PA46

Weight Class: ________
Climb Rate: _____________ fpm
Speed: ______________kts M
Descent Rate: ___________ fpm
Engines:
Number ________
Type ___________

Comments: ____

29 Old Designator AV8 New Designator HAR

Weight Class: ________
Climb Rate: ____________ fpm
Speed: ______________kts M
Descent Rate: __________ fpm
Engines:
Number ________
Type ___________

Comments: ____

30 Old Designator B767 New Designator B767

Weight Class: ________
Climb Rate: ____________ fpm
Speed: ______________kts M
Descent Rate: __________ fpm
Engines:
Number ________
Type ___________

Comments: ____

APPENDIX B

Summary Estimates and Number of Observations

Designator	Familiarity Rating	Speed	Climb Rate	Descent Rate		Weight Class	Engine Number	Engine Type
A3								
N	29	15	14	13	***N***	17	16	16
Mean	.03	377	2989	2627	**Mode**	Large	2	Jet
SD	.19	116	1480	1104				
A300								
N	29	27	25	24	***N***	28	28	28
Mean	1.83	465	2580	2542	**Mode**	Large	2	Jet
SD	.47	42	865	849				
A310								
N	30	28	26	26	***N***	29	29	29
Mean	1.73	461	2496	2665	**Mode**	Large	2	Jet
SD	.52	40	702	822				
A320								
N	30	29	28	27	***N***	30	30	30
Mean	1.87	472	2714	2530	**Mode**	Heavy	2	Jet
SD	.35	32	766	716				
AC50								
N	30	28	23	23	***N***	30	30	30
Mean	1.20	196	1128	1309	**Mode**	Small	2	Piston
SD	.61	56	402	531				
B52								
N	30	28	25	27	***N***	30	30	30
Mean	.57	475	2180	2341	**Mode**	Heavy	8	Jet
SD	.63	38	610	760				
B757								
N	29	29	27	26	***N***	30	30	30
Mean	1.97	474	2915	2738	**Mode**	Heavy	2	Jet
SD	.19	30	761	860				
B767								
N	30	28	28	27	***N***	30	29	29
Mean	1.90	480	2893	2807	**Mode**	Heavy	2	Jet
SD	.31	35	762	873				
BE36								
N	29	25	26	26	***N***	29	29	29
Mean	1.55	163	1006	1193	**Mode**	Small	1	Piston
SD	.51	21	254	502				
BE58								
N	30	29	26	27	***N***	30	30	30
Mean	1.53	191	1096	1250	**Mode**	Small	2	Piston
SD	.51	32	293	388				
C141								
N	30	24	27	27	***N***	29	29	29
Mean	.87	450	2320	2204	**Mode**	Heavy	4	Jet
SD	.63	38	821	691				

Designator	Familiarity Rating	Speed	Climb Rate	Descent Rate		Weight Class	Engine Number	Engine Type
C2								
N	29	11	9	9	***N***	11	11	11
Mean	.14	320	1628	1522	**Mode**	Large	2	Jet/Turbo-Prop*
SD	.35	113	762	616				
C208								
N	29	29	27	24	***N***	29	29	29
Mean	1.21	177	981	1010	**Mode**	Small	1	Piston
SD	.68	39	286	297				
C560								
N	29	27	23	25	***N***	29	29	29
Mean	1.90	393	1985	2160	**Mode**	Large	2	Jet
SD	.31	63	602	843				
C650								
N	30	27	28	28	***N***	30	30	30
Mean	1.83	472	3148	3166	**Mode**	Large	2	Jet
SD	.38	40	1127	1167				
C97								
N	30	19	18	18	***N***	21	20	20
Mean	.27	376	1892	2103	**Mode**	Heavy	4	Jet
SD	.58	105	698	793				
D328								
N	29	18	16	16	***N***	20	20	20
Mean	.62	272	1897	1847	**Mode**	Large	2	Turbo-Prop
SD	.82	64	796	744				
E120								
N	30	24	17	26	***N***	29	27	28
Mean	1.20	258	1347	1654	**Mode**	Large	2	Turbo-Prop
SD	.66	28	221	534				
F111								
N	30	21	22	25	***N***	27	28	28
Mean	.27	500	4005	4540	**Mode**	Large	2	Jet
SD	.58	35	1464	2272				
F16								
N	29	24	20	24	***N***	30	30	29
Mean	1.17	500	4685	5333	**Mode**	Large	1	Jet
SD	.71	41	1414	2448				
HAR								
N	30	24	23	24	***N***	27	28	28
Mean	.14	473	3961	4221	**Mode**	Large	2	Jet
SD	.38	62	1375	1731				
JSTB								
N	29	27	22	24	***N***	28	27	28
Mean	1.31	305	2052	2150	**Mode**	Large	2	Turbo-Prop
SD	.71	84	686	843				
L101								
N	30	27	25	28	***N***	29	29	29
Mean	1.43	492	2284	2386	**Mode**	Heavy	3	Jet
SD	.68	33	550	739				

* Bimodal

Designator	Familiarity Rating	Speed	Climb Rate	Descent Rate		Weight Class	Engine Number	Engine Type
LJ55								
N	30	29	26	26	***N***	30	29	30
Mean	1.77	464	3502	3633	**Mode**	Large	2	Jet
SD	.50	39	1108	1320				
MD11								
N	29	28	27	27	***N***	29	29	29
Mean	1.59	478	2478	2537	**Mode**	Heavy	2	Jet
SD	.68	42	615	730				
MD80								
N	30	29	24	26	***N***	30	30	30
Mean	1.93	453	2144	2315	**Mode**	Large	2	Jet
SD	.25	27	429	716				
PA46								
N	30	26	25	24	***N***	27	27	27
Mean	1.33	203	1180	1265	**Mode**	Small	1	Piston
SD	.48	37	358	447				
SF34								
N	30	25	22	20	***N***	27	27	27
Mean	1.30	253	1673	1615	**Mode**	Large	2	Turbo-Prop
SD	.65	29	388	409				
T38								
N	30	26	22	25	***N***	29	29	30
Mean	.93	488	5007	5280	**Mode**	Small	2	Jet
SD	.87	44	1505	2156				
V10								
N	30	20	21	20	***N***	23	23	23
Mean	.13	224	1412	1425	**Mode**	Small	2	Turbo-Prop
SD	.43	47	672	535				

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